Man Eats Forest

Agricultural Demand and Amazon Deforestation

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Motivation

- Amazon **deforestation** continues to be an issue,
- Agriculture has a large **deforestation footprint**; the *Brazilian beef industry* in particular is ...
  - *'the proximate cause of 70% of deforestation'*[a]
  - *'linked to deforestation that accounts for a fifth of land use emissions from the tropics'*[b]

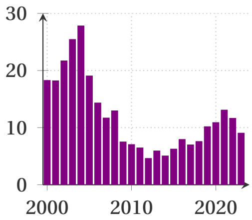

Figure 1: Deforestation in the Brazilian Amazon (in 1,000 km^2).

a. MapBiomas 2023.
b. Pendrill et al. 2019.

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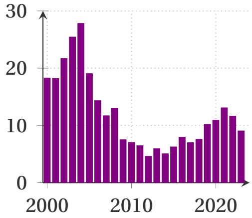

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- However, there's no frame for **causal interpretation**,
  - and naive regressions indicate **limited impacts**.
- We show that the **causal effect** of cattle on deforestation is **close to footprint estimates**.

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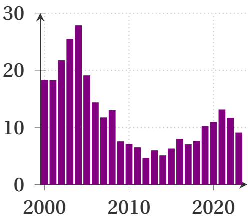

Figure 1: Deforestation in the Brazilian Amazon (in 1,000 km^2).

Motivation, Brazilian Amazon in 2000

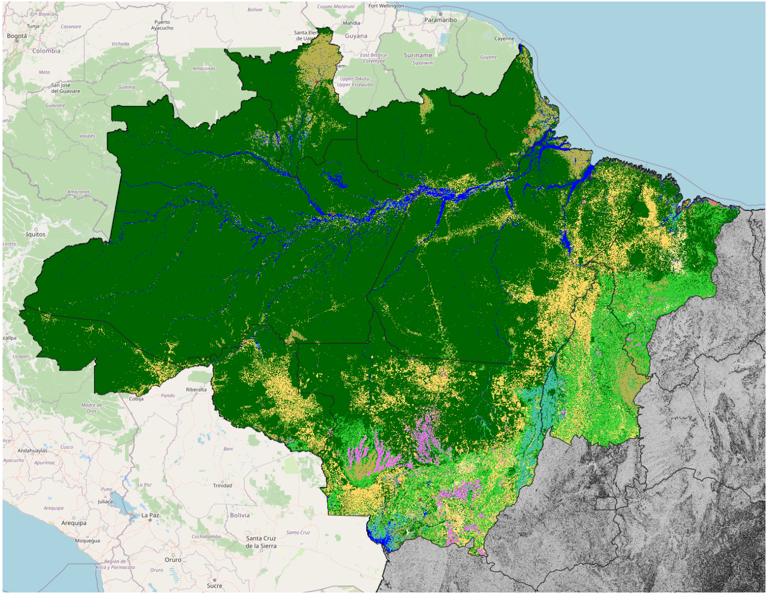

Figure 2: Land cover, including **forest**, **pasture**, and **croplands**, in the Brazilian Legal Amazon in 2000.

Motivation, Brazilian Amazon in 2022

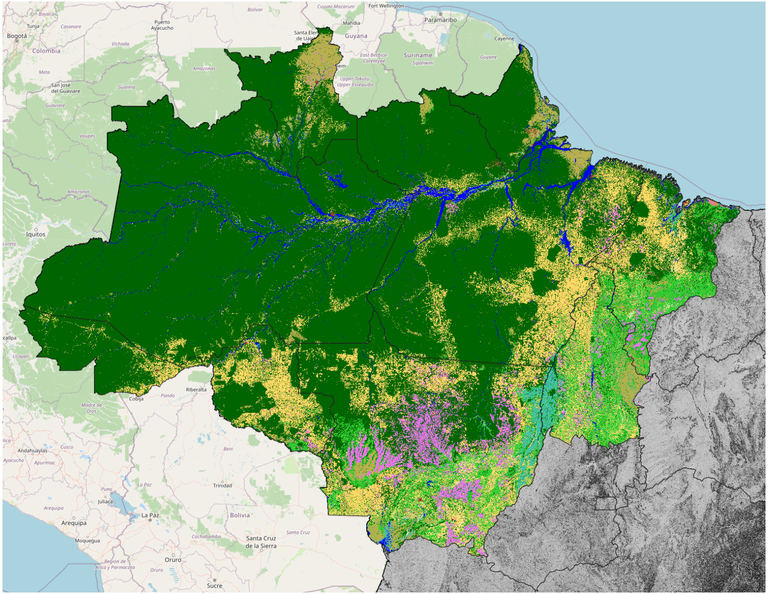

Figure 3: Land cover, including **forest**, **pasture**, and **croplands**, in the Brazilian Legal Amazon in 2022.

Background, Amazon deforestation in Brazil

- **Deforestation threatens** *biodiversity*, as well as local, regional, and global *climates*, and *livelihoods*.
- **Demand for land** stems primarily from *agriculture*,
  - with *soy and cattle* being the predominant factors.[1]
  - Mining and other agricultural products play a *limited role*.[2]

1. Carreira et al. 2024; Rajão et al. 2020.
2. See, e.g., Garrett et al. 2021; Giljum et al. 2022.
3. Fearnside 2017.
4. See, e.g., Kuschnig et al. 2023.

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- **Demand for land** stems primarily from *agriculture*,
  - with *soy and cattle* being the predominant factors.[1]
  - Mining and other agricultural products play a *limited role*.[2]
- Another important factor is speculative **land grabbing**, where
  - cattle serves as an intermediary to *feign ownership*,[3]
  - enabled by *poor property rights* and *anticipation effects*.
- Environmental policy and interventions have been **wavering.**[4].

1. Carreira et al. 2024; Rajão et al. 2020.
2. See, e.g., Garrett et al. 2021; Giljum et al. 2022.
3. Fearnside 2017.
4. See, e.g., Kuschnig et al. 2023.

Specification

Specification, model

We depart from a naive panel specification relating **deforestation** in hectare to changes in **cattle heads**:

$$\text{forest}_{i,t} = \beta\,\text{cattle}_{i,t} + \mathbf{x}'_{i,t-s}\boldsymbol{\gamma} + t\delta_i + \xi_t + \mu_i + e_{i,t}, \tag{1}$$

where i denotes municipalities, and t years, $\mathbf{x}$ covariates, t municipality-trends, and fixed effects are included.

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where i denotes municipalities, and t years, $\mathbf{x}$ covariates, t municipality-trends, and fixed effects are included.

We use an **instrument** to *causally identify* β, the effect of interest:

(2) $$\text{cattle}_{i,t} = \omega B_{i,t} + \mathbf{x}'_{i,t-s}\boldsymbol{\alpha} + t\delta_i^b + \xi_t^b + \mu_i^b + u_{i,t}.$$

Specification, instrument

Instrument construction

The (shift-share) **instrument** B, is constructed as

$$B_{i,t} = \sum_m \text{shift}_{m,t} \times \text{share}_{i,m,t=0}.$$

We rely on the **exogeneity of the shifts** for identification, and exploit the *shares* for relevance.

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The (shift-share) **instrument** B,[5] is constructed as

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We consider two sources of variation: Details

(a) changes in **international beef consumption**, coupled with
   - *export shares* per destination at the municipality level,

(b) changes in **Chinese beef consumption**, coupled with
   - *exposure to slaughterhouse* locations and initial stocks.

5. Also called 'Bartik' instrument; see Borusyak et al. 2022, for more information.

Specification, China shock and slaughterhouse exposure

Figure 4: Δ Chinese beef consumption.

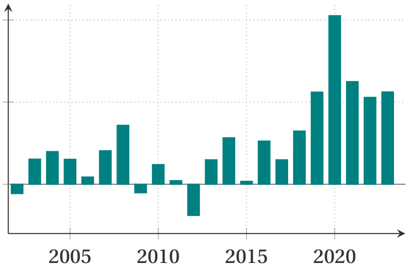
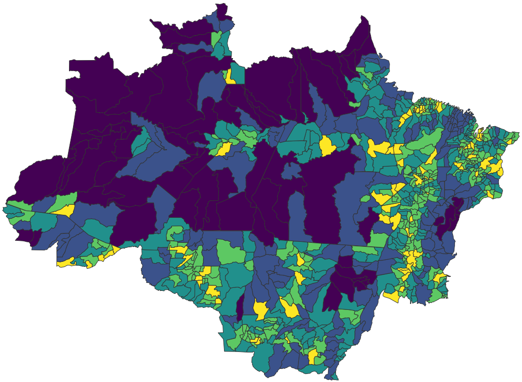


Figure 5: Slaughterhouse exposure in 2003.



Specification, covariates and heterogeneity

- The sample covers 808 municipalities of the **Legal Amazon**;
  - we also consider a subset covered by the *Amazon biome* (≈500).
- Deforestation changed over the **period 2003–2022**;
  - we consider splitting the sample per administration.
- **Variables considered** include ...
  - land cover and land use change (MapBiomas 2023), socioeconomic and agricultural data (IBGE 2022), environmental fines (IBAMA 2022), protected areas (UNEP-WCMC and IUCN 2022), climatological indicators (Vicente-Serrano et al. 2010), slaughterhouse locations (Vale et al. 2022), international beef consumption (FAO 2023), Brazilian beef exports (UN Comtrade 2022; Ermgassen et al. 2020).

Results

Results

	OLS			IV
Cattle	**-0.100**	**-0.103**	**-0.056**	
	(0.02)	(0.02)	(0.02)	
Covariates	None	Full	Full	
Specific trends	No	No	Yes	
Fixed effects	Yes	...		
$N \times T$	16,160	...		
F stat				

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Alternative instrument

Results

	OLS			IV		
Cattle	**-0.100**	**-0.103**	**-0.056**	**-0.466**	**-0.435**	**-0.582**
	(0.02)	(0.02)	(0.02)	(0.14)	(0.14)	(0.17)
Covariates	None	Full	Full	None	Full	Full
Specific trends	No	No	Yes	No	No	Yes
Fixed effects	Yes	…				
$N \times T$	16,160	…				
F stat				431.1	463.5	62.7

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

▸ Alternative instrument

Results, biome heterogeneity

	Amazon		Cerrado		*Savanna* ~
	OLS	IV	OLS	IV	
Cattle	**-0.057**	**-0.717**	-0.002	-0.169	
	(0.02)	(0.20)	(.002)	(0.12)	
Covariates	Full	…			
Specific trends	Yes	…			
Fixed effects	Yes	…			
$N \times T$	10,060	…	21,040	…	

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

▸ Regime heterogeneity

Results, biome heterogeneity

	Amazon		Cerrado		*Savanna* ~	
	OLS	IV	OLS	IV	OLS	IV
Cattle	**-0.057**	**-0.717**	-0.002	-0.169	**-0.009**	**-0.288**
	(0.02)	(0.20)	(.002)	(0.12)	(.002)	(0.14)
Covariates	Full	…				
Specific trends	Yes	…				
Fixed effects	Yes	…				
$N \times T$	10,060	…	21,040	…		
F stat		33.8		13.0		13.0

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

▸ Regime heterogeneity

Results, intensification

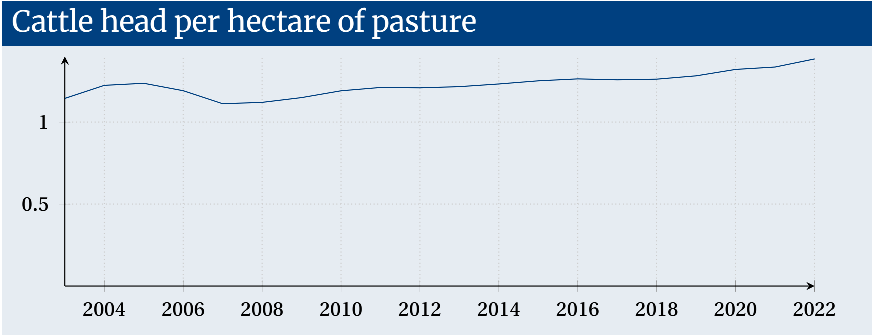
	Legal Amazon		Amazon biome	
	OLS	IV	OLS	IV
Cattle per pasture	**0.102**	**0.527**	**0.158**	**0.861**
	(0.03)	(0.09)	(0.05)	(0.14)
Covariates	Full	…		
Specific trends	Yes	…		
Fixed effects	Yes	…		
$N \times T$	16,160	…	10,060	…
F stat		73.9		46.4

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Conclusion

Discussion, effect size

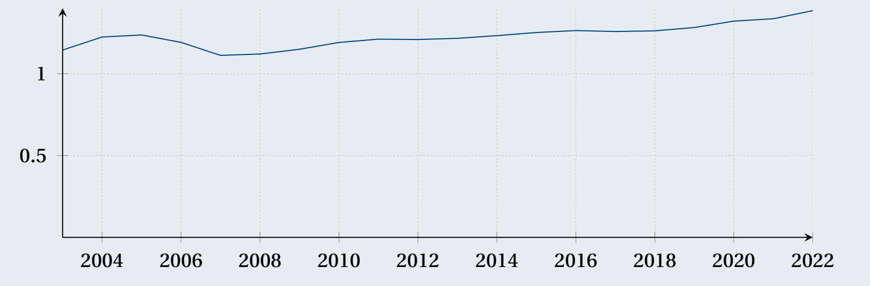
- *Stocking rates* suggest that **each cow** requires **roughly one+ hectares** of grazing area (see Samuel and Dines 2023).
- The reported **cattle per pasture** fall below that.



Discussion, effect size

- *Stocking rates* suggest that **each cow** requires **roughly one+ hectares** of grazing area (see Samuel and Dines 2023).
- The reported **cattle per pasture** fall below that.
- Naive estimates suggest **decoupling** of cattle and land.
- Our **instrumented estimates** are much closer to this **physical boundary** suggested by footprint analyses.

Cattle head per hectare of pasture



Discussion, implications

- The beef industry is considered a **driver of economic growth**
  - Monitoring *supply chains* complicated
- **Land use externalities** lie at the heart of climate change
  - Beef has a *caloric efficiency* of 1.9%[a]
- Few interventions **disincentivize** the drivers of deforestation

a. Alexander et al. 2016.

- The beef industry is considered a **driver of economic growth**
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- Few interventions **disincentivize** the drivers of deforestation

Table 1: Land use in m^2 for nutritional needs.[b]

	beef	cheese	eggs	nuts	potatoes
2,000 kcal	239.0	45.4	8.7	4.2	2.4
100g protein	163.6	39.8	5.7	7.9	5.2

a. Alexander et al. 2016.
b. Poore and Nemecek 2018.


Figure 6: Prussia was onto something.

Conclusion

In this presentation, we …

- dove into how **agriculture drives deforestation** in Brazil,
- found **considerable impacts of cattle ranching**,
  - driving around 63% of *observed deforestation*,
  - at 1  $\approx$ 1 hectare,
- which are **underestimated** without proper identification.

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In this presentation, we …

- dove into how **agriculture drives deforestation** in Brazil,
- found **considerable impacts of cattle ranching**,
  - driving around 63% of *observed deforestation*,
  - at 1  ≈ 1 hectare,
- which are **underestimated** without proper identification.

Thank you! — we're happy for any feedback!
You can find the slides, and follow the paper (and my related JMP on **deforestation spillovers**) online.

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Instrument construction I ◂ Return

We construct our instrument $B_{i,t}$ using …

- **shares** from a municipality's distance to the next slaughterhouse, interacted with the share of all pasture area.

$$\text{share}_{i,t=0} = \exp\{-\text{dist}_{i,t=0}\} \times \frac{\text{pasture}_{i,t=0}}{\sum_n \text{pasture}_{n,t=0}}.$$

  - Pastures expand near infrastructure and cleared land.
  - Transport costs determine profitability, and slaughterhouses are a necessary destination for cattle.
- **shifts** from changes in Chinese beef consumption.

$$\text{shift}_t = \nabla \text{beef}_{t-1}^{CHN}.$$

  - The demand is *relevant to* Brazilian agricultural products (FAO 2023), but doesn't affect Amazon deforestation in other ways.

Instrument construction II ◂ Return

The second instrument $B_{i,t}$ uses …

- beef consumption changes in *export destinations* $m = 1, \ldots M$

$$B_{i,t} = \sum_m \text{share}_{i,m,t=0} \times \text{shift}_{m,t}$$

$$\text{share}_{i,m,t=0} = \text{share}_{i,t=0} \times \frac{\text{exports}_{i,m,t=0}}{\text{exports}_{i,t=0}},$$

- where $\text{share}_{i,t=0}$ is defined by initial stocks and/or exposure to slaughterhouses, and
- $\text{shift}_{m,t}$ is the growth in beef consumption in m.
- Export shares are at the municipality level (available from Ermgassen et al. 2020), but are *only available for the second half* of the period considered.

Results, export-share instrument ◂ Return

	OLS		Export IV	
Cattle	**-0.109**	*-0.015*	**-0.381**	**-0.130**
	(0.03)	(.008)	(0.10)	(0.03)
Covariates	Full	…		
Specific trends	No	Yes	No	Yes
Fixed effects	Yes	…		
$N \times T$	9,696	…		
F stat			56.8	19.8

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, regimes

◂ Return

	2003–2015				2016–2022			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Cattle	**-0.088**	*-0.066*	**-0.389**	**-0.361**	**-0.142**	-0.015	**-0.510**	-0.267
	(0.02)	(0.02)	(0.09)	(0.11)	(0.04)	(0.01)	(0.13)	(0.29)
Covariates	Full	…						
Specific trends	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	Yes	…						
$N \times T$	10,504	…			5,656	…		
F stat			207.7	101.5			385.0	13.3

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.